```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler
from sklearn.ensemble import RandomForestRegressor
from sklearn.model_selection import train_test_split, KFold, cross_val_score, cross_validate
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score, make_scorer
```

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force_remount=True).
```

Step 1: Input the processed data

```
data = pd.read_csv('/content/drive/MyDrive/Data testing with IDXExchange/data_filtered-6nd-log_ClosePrice.csv')
```

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 79543 entries, 0 to 79542
Data columns (total 17 columns):
 #   Column                    Non-Null Count  Dtype  
---  ------                    --------------  -----  
 0   AttachedGarageYN          79543 non-null  float64
 1   BathroomsTotalInteger     79543 non-null  float64
 2   BedroomsTotal             79543 non-null  float64
 3   FireplaceYN               79543 non-null  float64
 4   GarageSpaces              79543 non-null  float64
 5   Latitude                  79543 non-null  float64
 6   LivingArea                79543 non-null  float64
 7   Longitude                 79543 non-null  float64
 8   LotSizeSquareFeet         79543 non-null  float64
 9   NewConstructionYN         79543 non-null  float64
 10  ParkingTotal              79543 non-null  float64
 11  PoolPrivateYN             79543 non-null  float64
 12  Stories                   79543 non-null  float64
 13  ViewYN                    79543 non-null  float64
 14  ListingContractDate_month 79543 non-null  float64
 15  Age                       79543 non-null  float64
 16  log_ClosePrice            79543 non-null  float64
dtypes: float64(17)
memory usage: 10.3 MB
```

Train-Test Split

Features/Target:

- `X`: All features except `log_ClosePrice`
- `y`: Transformed target (`log_ClosePrice`)

Split:
80% train / 20% test

- Random state fixed (42) for reproducibility

Purpose:
Creates evaluation framework for model development

```
X = data.drop(['log_ClosePrice'], axis=1)
y = data['log_ClosePrice']
```

```
# Step 2: Random train-test split (80% train, 20% test)
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42
)
```

Modeling Pipeline

Components:

1. `StandardScaler`: Normalizes all features
2. `RandomForestRegressor`:
    - 30 trees (`n_estimators=30`)
    - Fixed random state (`42`) for reproducibility

Design:
Single pipeline ensures:

- Consistent preprocessing for train/test
- Avoids data leakage
- Simplified model deployment

```
# Step 3: Define pipeline
pipeline = Pipeline([
    ('scaler', StandardScaler()),
    ('rf', RandomForestRegressor(n_estimators=30, random_state=42))
])
```

Model Validation

Method:
5-fold cross-validation with:

- Shuffled splits (`shuffle=True`)
- Fixed random state (`42`)

Metrics Reported:

- **RMSE**:
  `{mean:.2f} ± {std:.2f}`
- **MAE**:
  `{mean:.2f}`
- **R²**:
  `{mean:.4f}`

Purpose:
Robust performance estimation before final test evaluation

```
# Step 4: Cross-validation on training set
kf = KFold(n_splits=5, shuffle=True, random_state=42)


mse_scores = cross_val_score(pipeline, X_train, y_train, cv=kf, scoring='neg_mean_squared_error')
rmse_scores = np.sqrt(-mse_scores)

print("Cross-validated RMSE scores on Training Set:", rmse_scores)
print(f"Average RMSE: {rmse_scores.mean():.2f}")
print(f"Standard Deviation of RMSE: {rmse_scores.std():.2f}")
```

```
Cross-validated RMSE scores on Training Set: [0.21286903 0.18018384 0.17441161 0.18330647 0.17211637]
Average RMSE: 0.18
Standard Deviation of RMSE: 0.01
```

```
# Optional: Other metrics
scoring = {
    'mae': make_scorer(mean_absolute_error),
    'mse': make_scorer(mean_squared_error),
    'r2': make_scorer(r2_score)
}


results = cross_validate(pipeline, X_train, y_train, cv=kf, scoring=scoring)

print(f"MAE scores: {results['test_mae']}")
print(f"Average MAE: {np.mean(results['test_mae']):.2f}")

print(f"RMSE scores: {np.sqrt(results['test_mse'])}")
print(f"Average RMSE: {np.mean(np.sqrt(results['test_mse'])):.2f}")
```

```
print(f"R² scores: {results['test_r2']}")
print(f"Average R²: {np.mean(results['test_r2']):.4f}")
```

```
MAE scores: [0.11683174 0.1169057  0.11387609 0.11552286 0.11511504]
Average MAE: 0.12
RMSE scores: [0.21286903 0.18018384 0.17441161 0.18330647 0.17211637]
Average RMSE: 0.18
R² scores: [0.84315796 0.88446971 0.88799685 0.88116587 0.89167799]
Average R²: 0.8777
```

Final Model Evaluation

Process:

1. Trained pipeline on full training set
2. Predicted on held-out test set

Test Metrics:

- **MAE**: `{value:.4f}`
- **MSE**: `{value:.4f}`
- **RMSE**: `{value:.4f}`
- **R²**: `{value:.4f}`

Purpose:
Unbiased performance estimate of production-ready model

```
# Step 5: Final model training and evaluation on test set
pipeline.fit(X_train, y_train)
y_pred_test = pipeline.predict(X_test)

mae_test = mean_absolute_error(y_test, y_pred_test)
mse_test = mean_squared_error(y_test, y_pred_test)
rmse_test = np.sqrt(mse_test)
r2_test = r2_score(y_test, y_pred_test)

print("\n--- Final Evaluation on Test Set ---")
print(f"MAE: {mae_test:.4f}")
print(f"MSE: {mse_test:.4f}")
print(f"RMSE: {rmse_test:.4f}")
print(f"R² Score: {r2_test:.4f}")
```

```

--- Final Evaluation on Test Set ---
MAE: 0.1131
MSE: 0.0295
RMSE: 0.1718
R² Score: 0.8907
```

Prediction Visualization

Plot Components:

- Points: Actual vs Predicted values (`log_ClosePrice`)
- Red line: Perfect prediction reference

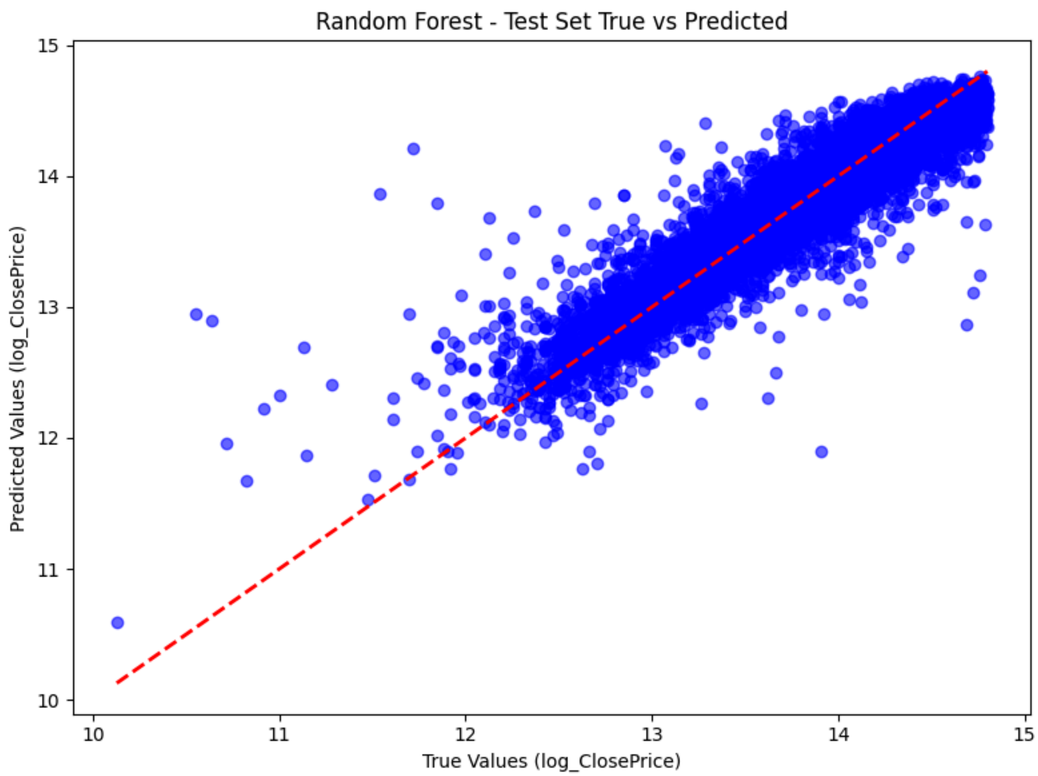
Key Insights:

- Vertical spread shows prediction error magnitude
- Cloud tightness indicates model accuracy
- Outliers visible as distant points

Purpose:
Visual diagnostic beyond numeric metrics

```
# Step 6: Plot True vs Predicted on Test Set
plt.figure(figsize=(8, 6))
plt.scatter(y_test, y_pred_test, color='blue', alpha=0.6)
plt.plot([min(y_test), max(y_test)], [min(y_test), max(y_test)], color='red', linestyle='--', lw=2)
plt.xlabel('True Values (log_ClosePrice)')
plt.ylabel('Predicted Values (log_ClosePrice)')
plt.title('Random Forest - Test Set True vs Predicted')
```

```
plt.tight_layout()
plt.show()
```



USD Price Prediction Plot

Transformation:
Converted predictions from log-scale back to original USD prices

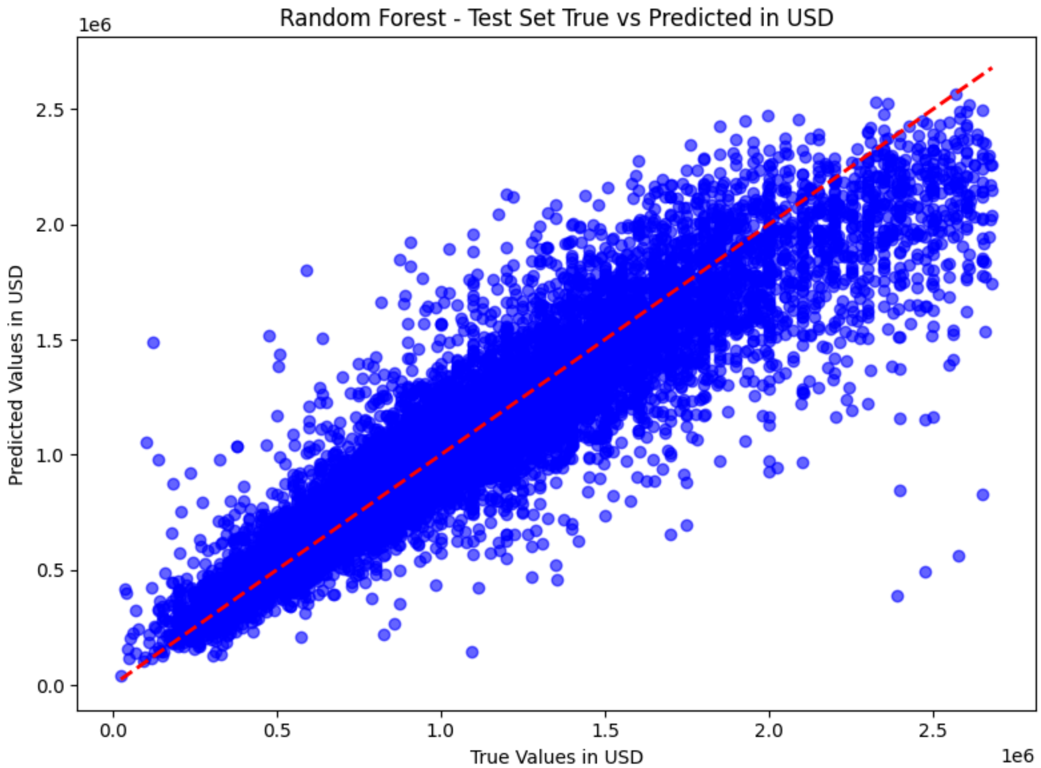
Key Features:

- Points show actual vs predicted home values
- Red line represents perfect predictions
- Axes now in interpretable USD

Business Value:
Enables direct evaluation of dollar-value accuracy

```
# Convert from log scale back to original price scale
y_test_actual = np.exp(y_test)
y_pred_actual = np.exp(y_pred_test)


# Step 6: Plot True vs Predicted on Test Set
plt.figure(figsize=(8, 6))
plt.scatter(y_test_actual, y_pred_actual, color='blue', alpha=0.6)
plt.plot([min(y_test_actual), max(y_test_actual)], [min(y_test_actual), max(y_test_actual)], color='red', linestyle='--', lw=2)
plt.xlabel('True Values in USD')
plt.ylabel('Predicted Values in USD')
plt.title('Random Forest - Test Set True vs Predicted in USD')
plt.tight_layout()
plt.show()
```



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